Overnight Trip Choice for Marine Anglers

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1. Introduction: Choices with Multiple Destinations and Multiple Days.

This report estimates the economic value of access to sites in the New England and Middle Atlantic states (Maine through Virginia) and changes in the availability of fish caught for recreational purposes for anglers on overnight trips in 1994. It follows a similar study (Hicks *et al*.) that uses a random utility model to estimate similar values for anglers on day trips. Both studies rely on the same survey datasets, the Marine Recreational Fishing Statistical Survey (MRFSS) and an associated economic survey completed in 1994. The Hicks *et al*. study exploits the single day trips while we analyze the overnight trips.

The emphasis in this report is inferring economic values from overnight trips using anglers' behavior. In previous work (McConnell and Strand), we used a contingent valuation approach to measuring the economic values for overnight trips. The approach was not completely satisfactory because it required an *ex post* evaluation of the fishing experience, sometimes as long as two months after a trip. One could use a contingent behavior question that was set in an *ex ante* mode but this data was not available. Further, it seems unnecessarily complex to use two methods of valuation—behavioral for the day trips and hypothetical for the overnight trips—when in fact one may be defensible. Contingent valuation has a role in analyzing more subtle components of fishing, but the basics of choice for single day trips and overnight trips—choosing among alternatives that differ by distance and the quality of fishing—are sufficiently similar to warrant the same approach.

Previous work on single day fishing trips, on the MRFSS data as well as in other settings, has proved the random utility model (RUM) to be an effective means of estimating site, mode and species choices, and calculating welfare gains or losses for changes in the conditions of catching fish. In past research, the modeling of overnight trips has proceeded differently from the single day trip. Several dimensions of overnight trips make them different from single day trips. First and perhaps most important, many overnight trips are not just for fishing, but are multiple purpose trips. The single day trip can more frequently be characterized as a single purpose trip, whereas overnight trips may be principally for business or family vacation. A second problem with overnight trips is the length of the trip, which becomes a choice variable. That is, a household decides not just where to go but how many days to stay. The length of stay has costs unconnected to the travel costs. The choice of trip destination may still be subject to the standard choice model, but the days per trip, or the total days per period is not a simple function of travel costs. The number and nature of the “blocks of time” available to the angler may be critical but are not easily measured.

The number of overnight trips is substantial. Of the 29745 marine recreational fishing trips intercepted (and recorded type of trip) during 1994 in New England and the Mid-Atlantic, over 5200 (or 19 %) reported that they were on an overnight trip. Because of this magnitude, it is essential to understand their behavior and account for them in the welfare analysis. One could simply expand the day trip estimates proportionately but they are likely differences between the two groups that would make such a procedure hazardous.

To give a notion of the difference between persons on overnight trips and on day trips, Table 1 is constructed. It shows the means and standard deviations of several characteristics of trips for persons who took overnight and single day trips. For description and analysis, the destination of a fishing trip is characterized in part by three fishing modes: shore, party/charter, and private boat. First, the percent of overnight trips fished from shore was approximately the same as for the sample of persons on day trips. However, the percentage of overnight trips taken from party/charter boats is nearly twice the percentage of day trips. The lower percent of trips using the private boat mode during the overnight excursions could arise because many anglers may not want to take their boat on a longer trip. Alternatively, the type of people taking the overnight trips may be different, with at least a portion of the sample being less committed to recreational fishing. This is borne out when we look at other individual characteristics of the anglers.

The overnight trips tend to occur during the warmer months (July-October), supporting the idea that these fishing trips are frequently part of a vacation. The total number of trips in the last two months for persons on overnight trips is approximately one-half of those taken by persons on day trips. The hours-spent fishing is slightly less and the money spent per individual on boat fees is slightly greater. The number of years fished is nearly 25% less for the persons on overnight trips and the respondents are slightly younger. Moreover, only about one-third of the sample of individuals on overnight trips stated that they would not have taken the trip if they could not fish on it. On the other hand, the hours worked per week and the household size of persons on overnight trips are quite similar to values for persons on one-day trips.

When we consider spatial differences, the likelihood of a site being the intercept site for someone on an overnight vis-à-vis a one-day trip increases in the states of Delaware, Maryland, Massachusetts, and Virginia. In other states it decreases. The presence of summer resort areas (such as Rehobeth, Dewey Beach, Ocean City, Cape Cod and Virginia Beach) in these states might explain the difference. New Jersey is an exception that could result from the concentration of the population (in Newark and Philadelphia) living close (within an hour) to the Atlantic and hence accessible for a single day trip.

The literature on travel cost models has handled multiple destinations and multiple day trips in a variety of ways. Researchers have often encountered these trips in otherwise homogeneous data. Often they are dispensed with casually, for example, by estimating separate demand functions or demand functions for trips of different length. Mendelson *et al*. treat the multiple destination problem more systematically by aggregating groups of site destinations into an additional alternative. This is perhaps a plausible treatment but does not address the multiple day nature of the MRFSS data. Parsons and Wilson provide a conceptually neat solution to the multiple destination trip by treating other destinations as incidental consumption and simply including the ‘price’ of this consumption in the site demand curve. Bell and Leeworthy confront a problem similar to ours. They model the number of days-spent beach going as a function of the costs per day plus the cost per trip. This approach for the continuous travel cost model makes a reasonable but still arbitrary allocation of the fixed trip costs to the individual beach days.

Table 1: Means of Sample and Individual Characteristics, Single and Overnight Trips during 1994.

Percent of Sample Intercepted in:	Overnight Trips (n=994)		Day Trips (n=3692)	
Shore	47.4%		44.6%	
Party/Charter	26.2		11.2	
Private Boat	26.5		44.2	
May-June	22.0		26.8	
July-August	45.8		40.8	
September-October	29.3		23.0	
November-December	2.90		8.50	
Connecticut	0.8		5.2	
Delaware	14.3		6.8	
Maine	4.3		2.7	
Maryland	8.1		6.2	
Massachusetts	29.6		17.7	
New Hampshire	1.3		2.2	
New Jersey	9.0		11.2	
New York	5.1		21.4	
Rhode Island	8.9		10.9	
Virginia	18.7		15.7	
Individual and Trip Characteristics	**Sample Mean**	**Percent of Sample Reporting**	**Sample Mean**	**Percent of Sample Reporting**
Days fished in last 2 months	3.33	99.7%	6.11	99.1%
Days in last two months visiting intercept site	2.38	15.0	4.99	19.2
Hours fished	3.64	100	3.78	100
Travel expenses	20.89	96.4	8.07	98.3
Lodging Expense	162.48	90.9	NA	NA
Boat fee	52.94	11.6	40.55	4.1
Years fished	15.31	34.5	19.53	28.5
Hours worked / week	44.41	27.6	44.70	28.2
Age	41.52	34.2	44.14	27.6
Household size	3.14	37.9	3.05	27.8
Income lost on fishing trip	540.07	4.0	164.94	1.2
Fishing necessary to trip? (1 if yes)	.29	99.9	-	-

Most recently, Shaw and Ozog have used a repeated nested multinomial logit approach that permits the angler to choose between no trip, a single day trip and a trip of greater than one day. While this approach combines the sample of persons on single day trips and overnight trips, it does not analyze the choice of time on a trip in a consistent manner. That is, during a fixed period of time, persons who choose single day trips have a greater number of choice occasions than anglers choosing to take two-week trips. A modeling of the time allocation choice over an extended period would be required to address the single and multiple day trip choice properly. That is beyond the scope of this project and the data on which the analysis rests.

We address the problem of the choice of where to go conditional on the angler having chosen the multiple-day trip. The Hicks *et al*. study has addressed the single day trips during 1994 and our analysis will allow a union of the two studies. By not examining the choice of how many trips to take and what type of trip (i.e. single day or overnight), we eliminate substitution possibilities for the angler. Although this is a shortcoming, we can assess the direction of the effects on welfare measures.

We face the same kinds of problems in modeling the site choice for multiple day trips. The two problems are 1) extra days spent on site do not depend on travel cost; 2) trips have multiple destinations and multiple purposes. Because the data place limitations on our approach, we do not deal with multiple destinations but instead use the distance from the angler's residence to the alternative sites to calculate the cost of a trip. We also do not attempt to model the length of the trip, limiting ourselves to the analysis of the trip destination. We investigate the impact of motives other than fishing on the estimated models. As part of the survey instrument, anglers are asked about other motives for making the trip. Responses to these questions can be used to help uncover the effects of different motives on site choice. However, the motive variable is not easily expanded beyond the sample. In the future, focus should be placed on understanding what household characteristics can be used to predict motives. With these characteristics that more readily available, the analysis can be extended beyond the sample with greater confidence of the results. In sum, our study uses origin-destination data from residence to fishing sites to explain the choice of location of overnight trips, much as the random utility models for single day trips.

In the following sections we describe and estimate a random utility model for overnight trips that involve fishing. We use the estimated parameters of these models to calculate various welfare measures. These measures provide estimates of anglers' aggregate willingness to pay for aspects of the marine sports fishing. One type of measurement pertains to changes in catch rates. Such changes might be induced by shifts in fishery policy or in changes in trends of pollution, which could reasonably be expected to change fish stocks. Another type of measurement relates to discrete changes in access to fishing sites. Some fishery management plans might call for a moratorium on catching various kinds of fish. Other events that could cause a change in access might be a regional oil spill, which would eliminate access to a large set of sites for a period of time. Ultimately the contribution of this research is in buttressing the economic value of marine sports fishing derived from single day trips. Ignoring the value of overnight trips means that a significant portion of sport fishing activity is not accounted for when values are estimated or that the incorrect "per trip" measure of value is applied when results are aggregated. An obvious candidate for the "per trip" value is the measure estimated for single day trips. Our results for various welfare measures are in fact quite different from the Hicks *et al*. results.

2. The Structure of the Model

As in previous studies, we consider the choice of sites, mode of fishing and species sought to be conditional on the individual having made the decision to take a fishing trip and use the information in that analysis to determine how many fishing trips they decide to take. The site/mode/species choice is discussed first.

2.1 The Random Utility Model

We follow the Hicks *et al.* model specification, using the historical catch rates rather than an expected catch rate based on characteristics of an angler. The Hicks *et al.* study obtained more realistic parameter estimates with the expected catch rates and there is reason to believe that anglers on trips with other purposes (like "family" vacations) are less likely to have clearly formed expectations. The overnight sample, for example, has a greater percentage of anglers who do not target any species.

Suppose that the angler gets satisfaction from attributes of the site. Travel is costly because of the opportunity cost of time and money. We model what species to fish for, how to fish for them and where to fish. In this report, the 'how to fish' is designated as mode. Hence the choices can be reduced to species, mode and site.

Anglers typically have a target species. Because there are so many species, we cannot estimate models for each of the species. Instead, the species are aggregated to four groups[1]:

1. Small game fish;
2. Bottom fish;
3. Flatfish;
4. Big game fish.

Anglers will choose to fish for one of these groups. Some anglers don't choose. They will be designated as non-seeking or non-target anglers, making the 5th group:

5. Non-target.

This makes the choice of species exhaustive.

There are many different ways to fish. From a boat an angler can troll, drift, or anchor, with or without chum. Fishing from shore can include surfcasting, pier fishing, jetty fishing, and others. We aggregate fishing into three types of modes:

1. Party or charter;
2. Private boat;
3. Shore.

This arrangement of choices gives 15 fishing alternatives—one for each of the three modes and one for each of the five species groups. The shore/big game combination is eliminated from consideration because it is not a feasible choice. Anglers would not typically seek big game fish from shore. This leaves 14 mode/species alternatives.

[1] The aggregation from species to groups is given in Appendix A.

The remaining choice is where to fish. In the New England and Middle Atlantic area, NMFS maintains hundreds of sites where anglers are intercepted. These sites are aggregated into 63 sites that are essentially counties or aggregates of counties[2].

The organization of the data partially determines the model of choices. We could have anglers pick species-mode-site at once. It is more parsimonious in terms of estimation and probably more realistic for the angler's decision to model the choice as two levels. First the angler picks the mode/species group combination. Given the mode/species group choice, the angler picks a site. This choice process can be modeled with the random indirect utility function:

(1) $$u_{mj} = v_{mj} + \varepsilon_{mj}$$

where

m = mode/species combinations: m = 1,…,14;

j = sites: j =1,…,63.

The u_{mj} is the angler's utility from the choice mode m, site j, with the v_{mj} being the deterministic part and the ε_{mj} being the component of preferences random to the economist but known to the angler. Ultimately an individual angler i chooses from an individual-specific choice set that we denote S_i. (In practice we find some mode/species combinations not relevant. Further we reduce by determining a reasonable choice set from the 63 aggregated sites and then sampling from the choice set according to Ben-Akiva and Lerman to reduce the estimation burden.)

To complete the model we have to specify both the deterministic element and the random element. The deterministic element has two components: the arguments and the functional form. The arguments are the attributes of the sites and the costs of fishing for the species group in the mode at the site. There is some variation in the preference function across modes. The preference function shifts for the private boat mode when an angler owns a boat. Essentially the deterministic part of the indirect utility function has the following structure:

(2) $$v_{mj} = v(\text{cost and time at site } j \text{ for mode/species } m, \text{catch rate for mode species } m).$$

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[2] The 63 sites are given in Appendix B.

This is in keeping with the idea that utility is generic. When we describe the site fully by giving the numerical value of its attributes we can determine the utility that can be gained there. This specification for the deterministic part of preferences can be motivated by supposing that anglers fix the total time they spend on trips independently of where they go. Then, given the total time, they compare the utility from various sites and modes.

The cost depends on the distance traveled, the opportunity cost of time and the mode/species combination. If the angler foregoes wages as part of the trip, then time has an opportunity cost. Otherwise time is an argument by itself. The mode/species costs vary also. Fishing from party or charter boats is more expensive than fishing from shore, obviously. The cost for site j, mode/species m is the sum of the travel costs and the mode/species cost. Hence a general parametric specification for v_{mj} is

(3) $$v_{mj} = \beta_{\$}(C_m + TC_j) + \beta_{time}(TT_j) + \beta_{fish}(Q_{mj}^{1/2}) + \beta_m$$

where the β's are parameters, C_m is the cost of fishing for mode/species group m, TC_j is the travel cost, TT_j is the travel time for anglers who have no explicit opportunity cost of time, and Q_{mj} is the historic catch rate for the mode/species group m at site j. When an angler does have an explicit opportunity cost of time, the utility function can be written

(4) $$v_{mj} = \beta_{\$}(C_m + TC_j + \lambda TT_j) + \beta_{fish}(Q_{mj}^{1/2}) + \beta_m$$

where λ is the opportunity cost of time[3]. Since v_{mj} is linear in income, the marginal utility of income is constant for the individual. Because $\beta_{\$}$ is estimated to be the same for all individuals, the marginal utility of income is the same across all individuals. But the marginal utility of catch rates goes down, because utility depends on the square root of the catch rate. The parameters have clear interpretations: $\beta_{\$}$ is the (negative of) the marginal utility of income, β_{time} is the marginal disutility of travel time, β_{fish} is the marginal utility of the square root of catch rates and β_m is simply a shift variable for utility at mode/species group m. The β_{fish} will vary by mode and by region. The $\beta_{\$}$ and β_{time} coefficients will be constant across mode, season and region. Note that some variables change across modes only and others change across site but not across mode. The travel cost and travel time are the same to all modes in the same site vicinity. The additional cost of fishing different

[3] We have assumed that the amount of time spent on site is predetermined and the same for all sites. Hence in the random utility formulation it falls out of the site choice problem.

mode/species groups does not depend on the site. Only the catch rates vary by site and mode/species group.

The stochastic term ε_{mj} we assume to have a generalized extreme value distribution. In a parsimoniously specified distribution, the extreme value gives the choice probabilities of site given mode as:

$$\text{(5)} \qquad \Pr\text{ob(site k from choice set S | mode/species group m)} = \frac{\exp(v_{km}/\theta)}{\sum_{j\in S}\exp(v_{jm}/\theta)}.$$

In expression (5), θ (which is identically equal to 1-σ in the Hicks *et al.* report) is a parameter of the distribution of ε_{mj}. The preference function in (3) can be written

$$\text{(6)} \qquad v_{mj} = \beta_\$ C_m + \beta_\$ TC_j + \beta_{time} TT_j + \beta_{fish} Q_{mj}^{1/2} + \beta_m$$

When the preference function has the form of equation (6), the conditional likelihood becomes

$$\text{(7)} \qquad \Pr\text{ob(site k | mode/species group m)} = \frac{\exp((\beta_\$ TC_k + \beta_{time} TT_k + \beta_{fish} Q_{mk}^{1/2})/\theta)}{\sum_{j\in S}\exp((\beta_\$ TC_j + \beta_{time} TT_j + \beta_{fish} Q_{mj}^{1/2})/\theta)}.$$

Note that the C_m term drops out, since it is the same for all sites in the mode, as do any terms such as the β_m, which relate to modes only. The estimation of (7) gives only relative values of parameters--$\beta_\$/\theta$, etc.

The probability of choosing a particular mode/species combination (say n) when the preference function is given by (3) is given by

$$\text{(8)} \qquad \Pr\text{ob(mode/species group n)} = \frac{\exp(\beta_\$ C_n + \beta_n + \theta I_n)}{\sum_m \exp(\beta_\$ C_m + \beta_m + \theta I_m)}$$

where I_n is the inclusive value for mode/species group n:

$$\text{(9)} \qquad I_n = \ln(\sum_{j\in S}\exp(v_{nj}/\theta)) = \ln(\sum_{j\in S}\exp((\beta_\$ TC_j + \beta_{time} TT_j + \beta_{fish} Q_{nj}^{1/2})/\theta)$$

Note that if C_m varied by site, it would appear in (7) and not (8). The data are not sufficiently rich to permit this. The two probabilities provide two ways of estimating the parameters: 1) sequential estimation, in which one first forms the likelihood function for site choice from (7) to obtain the parameter estimates in that probability and then uses the results in the likelihood function for mode/species choice found from (8) to estimate the remaining parameters; 2) full information, in which likelihood function for the probability of choosing a site and mode species combination is found using the product of (7) and (8). The FIML has several advantages over sequential estimation. It provides a gain in efficiency and it also gives the correct standard errors. Further, tests about coefficients that appear in both stages (such as $\beta_\$$) can only be carried out with FIML.

The structure of the models in (7) and (8) reveals several approaches to the handling of mode costs. We can see from the conditional probability in (7) that if we estimate the sequential model, mode costs will have no impact on the estimation of parameters in (7) if they are included at that level. Suppose however, that we do include mode costs in (7) and estimate sequentially. Then we would construct a likelihood function from a revised version of (8) for the mode/species group choice:

$$(10) \qquad \Pr ob(\text{mode/species group n}) = \frac{\exp(\beta_n + \theta I'_n)}{\sum_m \exp(\beta_m + \theta I'_m)}$$

where the revised inclusive value is

$$(11) \qquad I'_n = \ln(\sum_{j \in S} \exp((\beta_\$ (TC_j + C_n) + \beta_{time} TT_j + \beta_{fish} Q_{nj}^{1/2}) / \theta)$$

Since C_n is the same for all sites, we can rewrite this inclusive value as

$$I'_n = (\beta_\$ / \theta) C_n + I_n$$

so that $\theta I'_n = \beta_\$ C_n + \theta I_n$ (see equation 9) and we have the same model whether we include the mode cost at the first or second level of the sequential estimation procedure. If we do the sequential estimation procedure by forming the likelihood functions from (7) and (8), we get two independent estimates of $\beta_\$$. This is in fact what we do in our estimation procedure, and simple tests demonstrate that the two estimates are not significantly different from each other.

2.2 Day Trips, Overnight Trips, and the Influence of Distance

Trying to understand the total number of trips that an angler takes, whether for single day fishing or overnight trips, is an important component of measuring welfare, because large changes in the conditions of fishing bring changes in the aggregate level of trips, and this can imply large changes in welfare. Further, for short overnight trips, there may be substitution between single day trips and overnight trips. We limit our empirical analysis to the estimation and use of a random utility model. Here we discuss the issues that pertain to the next step of the analysis, estimating a model that predicts the number of multiple day trips for fishing, or the number of days fishing on multiple day trips.

From the previous discussions, two characteristics distinguish the overnight trips from the day trips: the multiple purpose-multiple destination nature of overnight trips and the additional choice of the number of days of fishing for an overnight trip. We discuss the implications of these characteristics on the overall demand for marine recreational fishing trips but we do not pursue the estimation of the number of trips as a function of the inclusive value and other characteristics of the anglers.

To begin, we ask the question—when does a trip become an overnight trip? This entails understanding the effect of distance on the length of a trip. When the length of the trip is sufficiently long, it becomes an overnight trip. We look intuitively at the relationship between the duration of a trip and the cost of the trip.

Define the full costs of a trip as the product of the amount of time and the opportunity cost of time. Let d be the distance, s be the speed of travel, c be the travel cost per mile, TT be the travel time, and T be the amount of time spent on site. Then the cost per trip, assuming that the angler is at an interior solution, trading an hour of work for an hour of leisure at the rate λ, is given by:

(12) $\lambda(2\cdot d/s + T)+2\cdot c\cdot d/s$

In the empirical analysis, $TT = 2\cdot d/s$, and for an interior solution, $TC = \lambda(2\cdot d/s)+2\cdot c\cdot d/s$. When the number of trips is chosen, λ can be taken as a constant value of time. Further, for short trips (but not necessarily long trips) it may also be constant with respect to trip time. With λ constant, the optimal number of trips would be determined by the trade-off between a Hicksian bundle, z, costing p, and recreation trips x, costing $\lambda(2\cdot d/s + T)+2\cdot c\cdot d/s$ per unit. If we compare the cost of a trip to site j to the cost at site j* all that will differ is the distance. The cost difference with be

$$(d_j - d_{j*})[\lambda(2/s) + 2\cdot c/s]$$

which is simply $TC_j - TC_{j*}$. When only the differences matter, the cost or amount of time on site disappears.

Now consider the costs when distance is considerable. Suppose that K is an upper limit on the amount of time that can be spent comfortably in all the activities of a day trip—travel time plus on site time. As in (12), the cost per trip is:

$$\lambda(2\cdot d/s + T)+2\cdot cd/s \quad \text{for } d \le (K-T)\cdot s/2.$$

But suppose that the trip length exceeds K. The effect of this longer day can be thought of as a higher (maybe much higher) opportunity cost of time because sleeping time is included in the travel time or the opportunity cost of time for an overnight stay becomes relevant. That is, as the single day trip lengthens, the opportunity cost of time rises. Then the cost per trip becomes

$$2\cdot c\cdot d/s+ \text{Min } \{\lambda\cdot K + \lambda^{*}(2\cdot d/s + T - K), \lambda\cdot K + C\}$$

where λ^{*} is the higher opportunity cost of time (induced by lost sleep, for example) and C is the lodging and associated costs of an overnight stay. As distance increases, costs go up, and eventually the type of trip changes from a single day trip to an overnight trip. This type of expression can be used to determine the choice set for single day trips. It also shows why the choice set for overnight trips will be much larger. The analysis can also be used to show that as distance from a site increases, the percent of overnight trips should increase relative to single day trips.

This simple analysis suggests that for a given angler, we would not expect to find single day trips and overnight trips to the same site. However, given the distances that we observe traveled on some overnight trips, it seems reasonable to infer that an angler might visit the same site on overnight trips as well as day trips. This phenomenon can be explained in part by the differences in motives for single day and overnight trips. The overnight trip may be vacation or business in part, even when fishing is an essential component. The difference in motive implies a different marginal utility. In that case a taste for variety will lead anglers to the observed behavior.

In past applications of random utility models, researchers have looked for ways to address the idea that when fishing circumstances change, not only will anglers change their choice of site, but they may also adjust the number of trips. While not theoretically justified, researchers have found the approach of modeling the number of trips as a function of the inclusive value as well as household characteristics practical and useful. When we consider the analogue for multiple day trips, the simple relationship between trips and the inclusive value breaks down for several reasons. First, to the extent that distance determines the inclusive value, the relationship between distance and the number of multiple day trips may not be monotonic. As the analysis above suggests, at low distances the number of multiple day trips is likely to be small. When distance increases, the number of multiple day trips increases, but eventually the number declines as distance become very large. With this kind of relationship, the inclusive value may not be a good predictor of multiple day trips.

A second issue in estimating a model for multiple day trips concerns the distinction between the number of trips and days per trip. For multiple day trips, anglers may fish more than one day. The number of days is analogous to the time spent on site in a more traditional travel cost model. One approach to the number of trips-number of days on site is to treat the two quantities as two endogenous variables derived from a utility maximization problem as in the formulation of an endogenous on-site time model[4]. Let T_i be the number of days on site, PT_i be its price, Z_i be the number of multiple day trips and H_i be a vector of household characteristics such as income, residential location, etc. Then the general system for determining the number of days and number of trips would be

$$Z_i = f(IV_i, PT_i, H_i)$$

$$T_i = g(IV_i, PT_i, H_i).$$

This model can be used to explain how trips and days on site change as fishing circumstances change, as reflected by the inclusive value, IV_i. Note that the computation of PT involves the opportunity cost of a day on site. It might for example, be computed from an angler's response to the question concerning lost wages per trip. Welfare effects would be calculated by determining how the number of trips changes as inclusive values change. The joint modeling should be handled with care, because in many cases the connection between the taking of the trip and fishing is quite tenuous.

[4] This model is developed in McConnell, 1992.

The third issue relates to why the modeling of trips with different durations is difficult. Some arbitrary but fixed and constant length of time (say a two-month period or a year) must constrain all anglers. As trips of different duration take place, a different number of choice occasions is possible within the fixed interval time. To be completely consistent, one would have to model the allocation of the fixed time limit for all anglers. This would require modeling decisions outside the typical recreation demand model and collecting data with far greater generality than is typically done.

3. Empirical Issues in Constructing the Model

Every econometric model has built into it strategic assumptions about functional form and specification as well as practical procedures for calculating exogenous variables that precede the estimation stage. The pre-estimation burden is especially great for random utility models. Part of the burden is in calculating the independent variables. These are needed for all sites in the choice set for each individual angler, not just the values at the site actually chosen. Variables such as travel cost are simply handled by making cost a function of distance. The individual angler is in practice motivated by perceived catch, but this is much harder to determine for all sites. Further even knowing which sites the individual actively considers is difficult.

There are three basic decisions to make about model construction:

1. the set of independent variables to include;
2. the calculation of independent variables;
3. the individual angler's choice set.

The first and second decisions are obviously related. Consider for example catch data. The ideal data would be the angler's subjective assessment of the number, kind and size of different species of fish that could be caught at each site. Instead we settle for the historic catch rate by groups of species. To make the model operational, and to complement the estimated models of single day trips by Hicks *et al*., we stick with the utility function specified in equation (6). The slight generalization involves the catch rate. We break the catch rate and catch rate coefficients so that some model/species groups have different coefficients. Further, we let the catch rate coefficient differ in the northern and southern regions of the study area. This is to accommodate the possibility that a different composition of species is present during any wave in the two areas. Species migrations would make this a good practice.

The utility function in (3) has several other modifications. We have reported the list of variables actually used estimation in Table 2. Most of the exogenous variables used in estimation are the same as those found in the Hicks *et al*. report and are calculated in the same way. However, it is useful to review what the factors are and how they are incorporated into the model.

A purely technical adjustment is imposed to account for aggregation within sites. Each site in the study, which is essentially counties, is aggregated across a number of NMFS intercept sites. To help correct for the aggregation problems that this creates, we introduce $\ln(M_j)$, where M_j is the number of individual sites within study site j. (See Ben-Akiva and Lerman.) Further, we have a mode/angler variable to account for the peculiarity of choices when an individual owns a boat. We create a variable as follows:

$Boat_{mi}$ = 1 if the angler i owns a boat and mode m is private boat fishing;
0 otherwise.

This variable captures the special attraction that private boat fishing will have for anglers who own their own boats.

In addition, we include as an attribute of the site the number of miles of beach for the site, which is activated only for waves 4 and 5. This accounts for the summer attractiveness of sites with many beaches, which would draw family vacationers. A distinction is also made regarding the attractiveness of sites during the colder months (May/June) and (November/December) based on their southerly location. During colder months, anglers are presumed to choose the more southerly sites.

Further, we use the indicator variable E, which takes a value of 1 if fishing is essential to the trip, as a means of modifying the influence of the catch rate and the number of fishing sites. We interact E with the catch of small game. We also interact E with ln(M), because the number of fishing sites is not operative when fishing is not

Table 2: Definitions and Sources of Exogenous Variables.

Variable	Definition	Mean from Chosen Site	Mean from Choice Set	Source
TC_j	Travel Cost for site j = $.30*distance + (income/2040)*time*interior Distance = roundtrip distance from PC Miler; Time: roundtrip travel time, predicted for all sites based on self-reported time and predicted time (distance/40miles per hour); Interior: indicator equals one if angler can work extra hours for extra pay.	83.69	145.98	Angler-specific data: Economic Add-on Survey Other data from PC Miler
TT_j	Travel time for site j = time*(1-interior)	2.27	3.95	PC miler
Q_{mj}	Mean of site catch rate mode/species m, site j.	2.87	3.14	MRFSS intercept survey
$Ln(M_j)$	Log of the number of intercept sites in the aggregate site j.	3.62	3.51	MRFSS Intercept Survey site list
$Boat_{mi}$	Indicator: equals one if angler i owns a boat and the mode is private rental; 0 otherwise.	.19	.12	Economic Add-on Survey
C_m	Access cost for mode/species group m.	9.19	26.93	Means from Economic Add-on Survey.
Bch_j	Miles of beach for site j.	.26	.18	National Estuarine Inventory
N_j	Indicator: equals one if site is located north of Delaware excluding Peconic Bay in New York.	.75	.74	MRFSS Intercept Survey
E_i	Indicator: equals one if fishing is essential for trip on which angler i is intercepted.	.63	.63	MRFSS Intercept Survey
W_{36}	Indicator: equals one if fishing occurs during waves 3 or 6.	.29	.29	MRFSS Intercept Survey
W_{45}	Indicator: equals one if fishing occurs during waves 4 or 5.	.71	.71	MRFSS Intercept Survey

essential for the angler. As a consequence of these individual decisions, the utility function for angler i for mode/species m, site j, wave t, becomes:

$$v_{mj}(i,t) = \beta_1 TC_{ij} + \beta_1 C_m + \beta_2 TT_j + \beta_5 Boat_{mi} + \beta_7 W_{45} \cdot Bch_j + \beta_9 E_i \cdot \ln(M_{jt}) + \beta_{12} W_{36} \cdot N + \beta_r E_i \cdot Q_{mjt}^{1/2} + \beta_s (1 - N \cdot W_{36}) Q_{mjt}^{1/2} \tag{13}$$

In this equation for the deterministic part of the utility function we include the individual observation index i, and the wave index t, as well as the mode/species index m and the site index j. The interaction between E and the catch rates and N and the catch rates varies across mode/species combination. Hence we can see the variables that change across observation for a given site and mode/species combination. Travel cost changes because the opportunity cost of time varies across individuals and because anglers live different distances from the alternatives. The argument TT changes because of differences in the location of residences and in a completely discrete way. If the angler is classified as not giving up wages, then time will enter directly. All the anglers not in the labor force will take the same amount of time to travel from a given residence to a given site. Further, in contrast to the Hicks *et al*. model, we do not have 'produced' fish, so that the catch rate does not vary across individuals. All anglers are assumed to form their expectations about catch using the same historical catch rate. Table 3 gives the complete specification of the deterministic portion of the utility function. Table 3 also contains $\beta_{11} \equiv \theta$, a parameter of the stochastic part of the utility function.

The catch rates are only operative under certain circumstances. The small game catch rate works only if fishing was essential (E=1) for taking the trip. The flatfish catch rate has no influence during waves 3 and 6 for N=1. The variable N is a binary indicator, taking on the value of zero for sites south of New Jersey, as well as Peconic Bay in New York. The idea that N works for waves 3 and 6 pertains to the tastes of anglers. During these months the cold weather matters most. Peconic Bay is a relatively protected area that attracts considerable fishing in the early spring and late fall. The basic species groups coefficients differ because anglers typically find some fish more

Table 3: The Deterministic Portion of the Indirect Utility Function

Variables in the conditional site choice utility model: v(mode, species, site j)					Variables in the mode/species choice utility model
V(PC,BG,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_3 Q^{1/2}_{BG,PC,i}$	$+ \beta_1 C_{BG,PC}$
V(PR,BG,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_3 Q^{1/2}_{BG,PR,i}$	$+ (\beta_5 BOAT + \beta_1 C_{BG,PR})$
V(PC,SG,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_4 E\, Q^{1/2}_{SG,PC,i}$	$+ \beta_1 C_{SG,PC}$
V(PR,SG,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_4 E\, Q^{1/2}_{SG,PR,i}$	$+ (\beta_5 BOAT + \beta_1 C_{SG,PR})$
V(SH,SG,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_4 E\, Q^{1/2}_{SG,SH,i}$	$+ \beta_1 C_{SG,SH}$
V(PC,FF,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_8 (1-N\, W_{36}) \times Q^{1/2}_{FF,PR,i}$	$+ \beta_1 C_{FF,PR}$
V(PR,FF,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_8 (1-N\, W_{36}) \times Q^{1/2}_{FF,PC,i}$	$+ (\beta_5 BOAT + \beta_1 C_{FF,PC})$
V(SH,FF,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_8 (1-N\, W_{36}) \times Q^{1/2}_{FF,SH,i}$	$+ \beta_1 C_{FF,SH}$
V(PC,BF,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_6 Q^{1/2}_{BF,PC,i}$	$+ \beta_1 C_{BF,PC}$
V(PR,BF,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_6 Q^{1/2}_{BF,PR,i}$	$+ (\beta_5 BOAT + \beta_1 C_{BF,PR})$
V(SH,BF,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_6 Q^{1/2}_{BF,SH,i}$	$+ \beta_1 C_{BF,SH}$
V(PC,NT,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_{10} Q^{1/2}_{NS,PC,i}$	$+ \beta_1 C_{NS,PC}$
V(PR,NT,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_{10} Q^{1/2}_{NS,PR,i}$	$+ (\beta_5 BOAT + \beta_1 C_{NS,PR})$
V(SH,NT,j)=	$\beta_1 TC_j$ +	$\beta_2 TT_j + \beta_7 W_{45} Bch_j + \beta_{11} W_{36} N$	$\beta_9 E \cdot \ln(M_j)$+	$\beta_{10} Q^{1/2}_{NS,SH,i}$	$+ \beta_1 C_{NS,SH}$

attractive to catch. For example, we would expect that most anglers would rather catch a striped bass (one of the small game) than a spot (one of the bottom fish).

For estimating the model we assume that the site choice is any site in the study area. In the single day model, the choice set is constrained by the amount of time that the angler has to fish, given the travel required. For example, in Hicks *et al*. the site choice set is determined by the sites within 400 miles. In the overnight data, anglers do not face the same time constraints. They can use up most of a day in travel and fish the next day. Hence we have no restrictions on the choice sets.

With no restrictions on the choice set, all anglers would be choosing from each of the 63 sites. This poses a problem for estimation, because such a large number of sites for each angler would make the estimation dataset quite large. For example, if each angler of the 900 plus anglers in the overnight survey chooses among 63 sites and the 14 alternatives of Table 3, then the size of the dataset would be greater than 790,000 rows. To reduce the size of the estimation dataset we sample sites, so that each site choice set is a sample of four, as well as the site actually chosen. Sampling also occurs at the mode/species level for estimation. Of the 14 alternatives, three are sampled, so that there are four alternatives at this level.

The rather small sampling—four out of 63 sites and three out of the 14 mode-species choices—is dictated by full information estimation of the model.   Estimating all of the parameters at once, rather than sequentially, requires that the number of alternatives in the dataset be fairly small. Otherwise convergence will be hard to obtain, and even when obtained will be quite time-consuming. Estimating the FIML is not without costs, however. The efficiency gains that FIML conveys on parameter estimation may well be lost because the number of alternatives needs to be reduced to accommodate the more complicated likelihood function. However, while sequential estimation with a larger choice set might appear to give more efficient estimates, it produces standard errors that are too small, and so part of the apparent increase in efficiency from more choices in the LIML estimates is illusory. The drawback of sequential estimation can be overcome by using a correction factor for the variance-covariance matrix.

The data for estimating the models comes from the MRFSS. This is a two part survey, one part being a field intercept survey and the other being a random digit telephone survey. An additional economic survey, called the economic add-on, originates with the intercept survey. The intercept survey selects anglers systematically, with known probabilities, for the purpose of identifying, counting, weighing and measuring catch. This survey also collects some angler information: the species targeted and the fishing frequency in the past two months and twelve months.

The economic add-on survey is administered to anglers in the intercept survey. It is designed to exploit the sampling properties of the intercept survey, and provide in addition some of the information needed from individuals for estimating behavioral models. The economic add-on has two components: the field questions that are administered as part of the intercept survey, and a telephone follow-up interview that gathers additional information from the angler. For travel cost and random utility models, the economic add-on survey provides information that is instrumental in calculating the cost of travel and the cost of time, as well as travel time. The observations for anglers' trips come from the economic add-on survey. The trip that is modeled in the random utility model is the trip on which the angler was intercepted.

The random digit telephone survey is a random survey of the coastal and near-coastal population. Its purpose is to determine the number of anglers in the population as well as the level of activity per angler. In combination, the intercept and the phone survey are used to estimate total catch by species, season, area and mode for recreational anglers. The random digit phone survey is executed throughout the year to cover the five two month periods: March-April, May-June, July-August, September-October, and November-December.

4. The Estimation of the Model.

The dataset for estimation includes the 984 anglers who were intercepted as part of an overnight trip. The FIML procedure was run in GAUSS. Table 4 shows the parameter estimates. These parameter estimates generally meet expectations about sign. The cost and time coefficients are negative and highly significant. The basic catch rates are positive. The estimate of the inclusive value coefficient (θ) is .797, and is significantly greater than zero and less than one at the 95% level of confidence. The interaction of private rental and the indicator variable for the ownership of a boat works strongly to influence choice. The empirical magnitude is such that if angler A without a boat has a 10% probability of choosing a site, then angler B, equal in all ways but owning a boat, would have about a 30% probability of choosing the same site.

As we demonstrated in Section 2, the coefficient on the mode costs should be equal to θ times the coefficient on travel costs because they are both just the negative of the marginal utility of income. In the estimation, these coefficients are constrained to be equal. The estimate of β_1 is -.0078, and this is quite low, indicating that the choice of sites is relatively unresponsive to increases in costs. This may be in part due to the multiple purpose nature of the trips. The low estimate of β_1 has the effect of raising the welfare estimates for whatever changes confront the anglers.

The catch rate coefficients determine the economic gains and losses from the changing the conditions of fishing. When divided by the marginal utility of income, these coefficients give the marginal value of increases in the historic catch rate. For example, for big game fishing, $\beta_3/\beta_1 \approx \$60$. This is not the value of catching another fish, but the value of increasing the historic catch rate by one, an improvement that would be quite substantial. Note that the estimates of catch rate coefficients are not comparable with the estimates in Hicks *et al*. In the single day trip model, the catch rate was an individual expected catch rate model.

5. The Calculation of Gains and Losses for Changes in Fishing Circumstances.

5.1 The Basic Theory

One of the advantages of the random utility model is its ability to provide welfare estimates for a variety of realistic policy scenarios. What makes the RUM work so well for welfare estimation is that it models how anglers choose among different alternatives. Because the utility from alternatives is assumed to be linear in income, equivalent and compensating variation are equal to willingness to pay, which we denote WTP. The WTP for a change in fishing circumstances is defined as the amount of money that makes the angler indifferent between the current situation and the changed situation. It is understood that if the change is worth paying for, then WTP represents the amount of money that anglers would pay to get the change. If the change reduces the fishing circumstances, the WTP represents the payment that would have to be made to the anglers for compensation for the losses that would be incurred for worsening circumstances, or the amount of income anglers would give up for improvements.

The calculation of WTP requires the exact formulation of the preference function. Because this function is random to the analyst, it is necessary to eliminate the

Table 4: Parameter Estimates For Random Utility Model.

Variable[a]	**Parameter**	**Estimate (t-ratio)**
Conditional Site Choice Model		
Travel Cost	$\beta_{\$}$	-.0098 (-10.4)
Travel Time	β_2/θ	-.280 (-8.22)
Beach Miles in Waves 4 and 5	β_7/θ	0.776 (5.91)
E·Ln(M)	β_9/θ	0.074 (0.93)
Big Game Catch	β_3/θ	0.794 (1.62)
E·Small Game Catch	β_4/θ	0.297 (1.17)
Bottom Fish Catch	β_6/θ	0.197 (1.76)
Flatfish Catch (except North in Waves 3 and 6)	β_8/θ	0.654 (7.18)
Non-targeting Species	β_{10}/θ	0.163 (2.46)
Wave 3 and 6·North Sites	β_{12}/θ	-1.066 (-7.43)
Mode/Species Choice Model		
Inclusive Value	$\hat{a}_{11} = \theta$	0.797 (10.5)
Boat	β_5	1.493 (11.2)
Access Cost	$\beta_{\$}$	-.0098 (-10.4)
χ^2 (all parameters=0) =821.3		

[a]Variables are defined in Table 2.

randomness and find the expected value of the maximum utility. Hanemann has this worked out for the nested multinomial logit:

(14) $V^*(i) = \text{Å}\{\max u(i)_{mj}\} = \ln\{\sum_{m}[\sum_{j \in S_i} \exp(v^*_{mj}(i)/\theta)]^{\theta}\}$

where * equals 1 for the change in circumstances and 0 for the initial circumstances and E is the expectations operator. The individual's deterministic portion of the utility function, $v^*_{mj}(i)$, is given in equation (13), with the detailed specification of Table 3. The WTP estimate for individual i is

$$WTP(i) = \ln\{[V^1(i)/V^0(i)]\}/\beta_{\$}.$$

Two observations on the calculation for the expected maximum utility: first, the full set of mode/species is included, so that the m goes from 1 to 14; second, the change is evaluated at the individual's full site choice set of 63 sites, not the sampled choice set.

5.2 Per Trip Gains and Losses

We calculate the welfare effects of three kinds of policy scenarios: loss of access in a state, a unit increase in the historic catch, and a 50% increase in historic catch. The loss of access to fishing in a state is designed to answer the often asked question "What is the economic value of recreational fishing?". The real answer to this question is that it depends on what is changing. But the access values help fill the political need for a sort of benchmark that gives some idea of the aggregate value of the activity, the 'importance' of recreational fishing. The welfare effects of catch rate changes are calculated to give insight into more pertinent policy questions, such as what would be the value of a program to enhance certain flatfish species or prohibiting fishing for tautog.

The scenarios for changes in catch rates have drawbacks. First, in applying a percent change, many sites are left out because they have zero catches, so that a percent change of any size means no change. This is especially true of big game catch rates. Second, adding a fixed amount to current catch rates often results in quite a large percent increase. Many sites and waves where one may expect zero catch will have at least 1 fish caught. Thus, use of models is best for analyzing a specific policy agenda when the policy proposed contains the biological situation (i.e. new catch rates) inherent with it.

Table 5 contains the estimates by season and state for the loss per trip for a representative angler. The next to the last column gives the mean across all waves while the last column gives the percent reduction in the choice set induced by the state closure. In general, the estimates are most strongly influenced by the size of the loss in terms of the extent of the market, the seasonality, and the attributes of the state and the

Table 5: Closure Of All Fishing Sites In A State: Mean Loss Per Trip.

State	May-June	July-August	September-October	November-December	Mean for All Waves	% Change in Choice Set
Virginia	$29.28	$30.13	$10.03	$15.89	$23.57	- 12.7%
Maryland	12.54	10.14	10.34	13.21	10.99	- 11
Delaware	11.70	6.87	4.67	9.91	8.32	- 06
New Jersey	4.11	4.64	10.86	6.44	6.32	- 12.7
New York	12.21	13.66	21.87	18.37	15.81	- 16
Connecticut	1.19	2.52	5.61	2.34	3.01	- 06
Rhode Island	2.21	5.46	5.44	2.53	4.45	- 08
Massachusetts	3.39	6.43	8.87	4.39	6.19	- 12.7
New Hampshire	.40	.50	.70	.30	.50	- 03
Maine	2.38	3.43	4.67	2.28	3.43	- 12.7

distribution of users. New Jersey has a long coastline, but since most of New Jersey's population is in the northern part of the state, near New York, the closure of New Jersey has a relatively low loss. The size of New York and the combination of size and being in the south for Maryland and Virginia make the loss from closing these states the greatest. The very brief coastal exposure of New Hampshire makes that the loss from the closure of that state quite small. Also, the estimated loss from closure of Delaware sites is small in the summertime but in May-June and November-December, they increase due to greater substitution from colder states during those period.

Tables 6 and 7 provide estimates of the gains per trip from improving the historic catch rate. Here we see the peculiar effects of the kinds of changes that we have specified. In Table 6, the estimates for a 50% increase are tabulated. The $4.51 figure for big game catch rate for Virginia gives the value of increasing the historic catch rate for big game species at fishing sites in all states, for anglers who were intercepted in Virginia. Despite the fact that the marginal value of improvements in the big game catch rate are higher than for the other species, the big game value is quite low. This is because in many cases the big game catch rate is zero, and so with a 50% increase it is still zero. The largest values for improvements in historic catch rates are realized for flat fish and bottom fish, where the initial catch rates are highest. They are greater than the small game values in part because values from enhanced small game catch arise only for anglers that consider fishing essential to the trip and from anglers that were not targeting species. The variation of the values of improvements in historic catch rates across states stems from spatial differences in the anglers who were intercepted in different states. These variations are quite small.

Table 6: A 50% Increase In Historic Catch Rates: Gains Per Representative Angler

State	Big Game	Small Game	Bottom Fish	Flat Fish
Virginia	$4.51	$3.36	$12.65	$11.04
Maryland	6.21	3.06	17.49	14.77
Delaware	6.11	4.05	19.02	16.72
New Jersey	6.84	3.87	20.58	16.15
New York	8.72	9.45	21.47	11.85
Connecticut	5.89	6.55	21.12	20.37
Rhode Island	9.04	7.82	21.86	12.83
Massachusetts	3.39	6.78	21.32	14.23
New Hampshire	10.00	3.75	19.91	11.87
Maine	6.05	4.40	17.79	15.54
All States	6.69	4.60	18.02	13.97

Table 7 gives the value of improving the historic catch rates by one fish for all sites, by state. This means that for those species groups that have very low or zero catch rates, the improvement is quite substantial. In particular we see that the welfare gains for big game fish are quite large, on the average about $55. In both Tables 6 and 7 the values for small game catch rate improvements are quite small. In part this reflects the specification that makes the small game catch rate operative only for anglers for whom fishing is an essential component of the overnight trip.

5.3 Aggregate Gains and Losses.

The values per trip are useful for understanding the nature of welfare losses under different circumstances. But for these losses to be useful in considering trade-offs, say between the costs of pollution control and the gain in the value of fishing, or commercial versus recreational fishing, they have to be aggregated. No existing estimates exist on the number of overnight trips taken (as opposed to the number of days fished on an overnight trip). We can make an estimate of the number of overnight trips by creating a sample ratio by wave of the number of days fished from anglers on overnight trips to the total

Table 7: An Increase Of +1 Fish in Historic Catch Rates:
Gains Per Representative Angler.

State	Big Game	Small Game	Bottom Fish	Flat Fish
Virginia	$42.91	$4.70	$4.84	$12.26
Maryland	55.07	3.87	17.49	15.14
Delaware	60.33	5.05	6.36	16.17
New Jersey	63.64	3.87	6.75	18.16
New York	64.86	10.18	7.44	11.85
Connecticut	63.51	7.87	6.10	15.44
Rhode Island	60.71	8.22	6.63	19.44
Massachusetts	61.17	6.78	6.15	18.32
New Hampshire	57.37	3.99	6.20	16.31
Maine	55.15	4.40	6.55	15.54
All States	55.59	5.26	6.03	16.00

number of days fished . This is then multiplied by the official NMFS's estimate of total trips by wave (Hicks *et al*.) to produce the total number of days fished by anglers on overnight trips. This number is then divided by our sample estimate of the number of days fished on an overnight trip to produce the total number of overnight trips.

One way of aggregating the values per trip is to compute the product of the number of trips and the value per trip. Table 8 gives the number of overnight trips by state and wave for 1994. In order to aggregate the values to the entire sample, we multiply the total number of overnight trips (last column) by the value per trip to get some understanding of the aggregate gains and losses from changes in fishing circumstances.

Table 9 gives an estimate of the aggregate losses that would occur if the recreational fishery were closed in each state, by wave. These estimates are a lower bound. The loss per individual would be greater for the second trip than for the first trip, and so on, and the statistics show that many anglers take more than one trip. The variation across state and wave is quite substantial, showing the effect of location and

Table 8: Number of Overnight Trips in the Northeast U.S. in 1994 (1000's of trips).

State	May-June	July-August	September-October	November-December
Virginia	73	90	39	5
Maryland	57	91	68	5
Delaware	16	26	12	2
New Jersey	82	206	122	13
New York	82	176	82	7
Connecticut	27	44	22	.4
Rhode Island	19	31	57	.4
Massachusetts	79	128	73	2
New Hampshire	17	10	2	n/a
Maine	15	27	11	n/a
Total	467	829	488	27.8

Table 9: Aggregate Willlingness to Pay to Avoid Loss of Sites in a State By Anglers on Overnight Trips, by State and Wave ($1000's).

State	May-June	July-August	September-October	November-December
Virginia	$13,673	$24,977	$4,894	$552
Maryland	$5,856	$8,406	$5,045	$459
Delaware	$5,463	$5,695	$2,278	$344
New Jersey	$1,919	$3,846	$5,299	$224
New York	$5,702	$11,324	$10,672	$639
Connecticut	$555	$2,089	$2,737	$81
Rhode Island	$1,032	$4,526	$2,654	$88
Massachusetts	$1,583	$5,330	$4,328	$152
New Hampshire	$186	$414	$341	n/a
Maine	$1,111	$2,843	$2,278	n/a

season on the value per trip and the number of trips. For example, a closure of New York state recreational fishing for the period July-August would mean a loss of $11 million, whereas a closure of New Hampshire for September-October would be a loss of about $341 thousand.

While it is possible to add up losses across seasons (or waves) to reach annual totals, this addition will yield lower bound estimates of the losses that are increasingly lower bounds as the degree of aggregation rises. The more alternatives that are closed, the more the angler's ability to substitute will be impaired. We can demonstrate this for sites, for example, by showing that the losses from a simultaneous closure of Virginia and Maryland exceed the sum of the losses from the closure of the individual states. Although we do not model the temporal choice, the same principle applies.

6. Cautions about the Welfare Estimates

The welfare estimates derived above are restricted in the sense that anglers are modeled to adjust only the destination of their trips, and not the type nor the number of trips. For example, when catch rates increase, it would be reasonable for some anglers to increase their fishing trips. Likewise, other anglers might increase their single day trips at the expense of multiple day trips. In the absence of such adjustments, the aggregate welfare measures are biased. If we consider only the effects of the adjustments in the number of trips, we can determine the direction of bias. When an improvement in fishing circumstances occurs, it is reasonable to suppose that anglers would increase the number of trips they would take. This is borne out by studies that demonstrate that the number of trips is an increasing function of the inclusive value, which increases with improved fishing circumstances. When welfare measures are aggregated across trips, without allowing the number of trips to increase, then the resultant estimate can be considered a lower bound to the true welfare estimate. A higher value would be achieved when anglers increased their level of activities.

The opposite occurs when fishing conditions deteriorate, whether because of site closings or reductions in catch rates. When fishing conditions decline, then it is also reasonable to believe that anglers would reduce their trips. In that case, the value per trip measure ought to be aggregated across a lower number of trips than the observed level. Hence the losses in fact are not as great as they appear to be when aggregated across a fixed number of trips. In both cases, whether the conditions improve or deteriorate, the under- or over-estimation is a consequence of the declining marginal value of trips. Further the actual situation is more complicated, because not only may anglers increase or decrease their trips, but they may also change the type—from single to multiple or vice versa.

7. Conclusions: Some Thoughts for Future Work

In this report we have estimated a random utility model and calculated the welfare effects from several types of changes. The model works in roughly the same way that the model of Hicks *et al*. for single day trips works. Anglers substitute among sites based on the costs, the catch of fish, and some measures of attractiveness of the sites. The model we have estimated embodies strong priors on the way in which catch and other variables influence the probability of choosing a particular site. Thus one may consider the model to be constructed, based on our notion of how reasonable anglers would behavior. It is not Bayesian in a formal sense, but it is most certainly not classical statistics either.

In past practices, the estimation of random utility models typically ended when researchers squeezed welfare measures out of the data. Very little sensitivity analysis has been carried out. This is especially true for MRFSS models, because the large size of the data set, computer constraints, and the difficulty of calculating a consistent set of catch rates have made the task rather monumental. As researchers gain experience and computer constraints fade, it is worth thinking about the more vulnerable areas of random utility models estimated on MRFSS data. We offer several suggestions, based on the idea that these models should provide insight into fisheries issues.

The specification of utility, as a function of costs, time and a measure of the quality of fishing, appears to capture the predominant forces in determining choices. Historic catch rates are calculated as the sum of landed fish of the appropriate species group divided by the number of anglers intercepted at the site. The catch rate is a compromise between what is feasible, and measures of the quality of fishing that more accurately capture the goals of anglers. For small game and even big game, the catch rate, which is essentially a count measure, may do reasonably well. Anglers care about the number of these fish. But even in these species groups, one big fish--say a 20 pound striped bass—is worth quite a number of small fish. When there is variation in the weight of the catch, then numbers may be misleading. For bottom fish, and to a degree, flat fish, the aggregate weight per trip may be a much better measure of quality than the number of fish caught per trip because anglers often fish for these species primarily for home consumption. Other measures of fishing quality are important for anglers. For example the biggest fish could be all that matters. It is a reasonable assumption that other measures are highly correlated with the catch rate, but this assumption has not been tested empirically. Given the extensive nature of the intercept data, a variety of different variables can be calculated and tested.

Fishing is quite different at different times of year. Fish stocks move seasonally, and fishing sites have vastly different appeal in different seasons because of cold or windy weather. Further, because species move seasonally, there are some gains from trying to understand behavior by season.

From a methodological view, random parameters logit (RPL) models are emerging (see Train). These models allow greater random heterogeneity among anglers. There are also quite demanding to estimate in terms of computer resources. But there are several ways in which the RPL would be worth testing. First, the coefficients on catch rates can easily are easily conceived as dispersed. Many anglers know only the slightest amount about what species to expect. Second, because of the size of the MRFSS dataset, it is necessary to sample alternatives. The efficacy of sampling when one estimates an RPL model remains to be explored.

These problems exist with or without consideration of the overnight or multple purpose trip. Maybe more relevant to the subject of our research is the information that would be useful for NMFS to collect to improve our understanding and analysis of overnight trips. We found that the purpose of the trip helps explain some of the angler's behavior. Unfortunately, we had information only on whether or not the angler would have taken the overnight trip if they could not fish. It might be informative to follow this question (for people who said fishing was not essential) with several questions concerning why they did take the trip and why the chose the site. Questions regarding second homes, mooring of boats or traditional family vacations could be revealing.

References

Bell, F.W. and V. R. Leeworthy. “Recreational Demand by Tourists for Saltwater Beach Days”. *Journal of Economics and Environmental Management*, 18(3):189-205.

Ben-Akiva, Moshe and Steven R. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, 1985.

Hanemann, W. M. “Welfare Analysis with Discrete Choice Models” Chapter 2 in (J. Herriges and C. Kling, eds.) *Valuing Recreation and the Environment*, Edward Elgar, 1999.

Hicks, Rob, Scott Steinback, Amy Gautam and Eric Thunberg “The Economic Value of New England and Mid-Atlantic Sportfishing in 1994”, National Marine Fisheries Service, 1998.

Kaoru, Y. ”Measuring Marine Recreational Fishing Benefits of Water Quality Improvements by the Nested Random Utility Model”, *Resource and Energy Economics,* 17:119-136, 1995

McConnell, K.E. and I.E. Strand “The Economic Value of Mid and South Atlantic Sportfishing” Report on Cooperative Agreement CR-811043-01-0 between the University of Maryland, the Environmental Protection Agency and the National Marine Fisheries Service. September, 1994.

McConnell, K. E. "The Problem of Onsite Time in the Demand for Recreation," *American Journal of Agricultural Economics*, November, 1992.

Mendelson, Robert O. John Hof, George Peterson, and Reed Johnson. ‘Measuring Recreation Values with Multiple Destination Trips’, *American Journal of Agricultural Economics* ,74 (November):926-33,1992.

Parsons, George and Aaron J. Wilson ‘Incidental and Joint Consumption in Recreation Demand’ *Agricultural and Resource Economics Review* 26(April):1-6,1997.

Provencher, Bill, and Richard C. Bishop. ‘An Estimable Dynamic Model of Recreation Behavior with an Application to Great Lakes Angling’ *Journal of Environmental Economics and Management,* 33(June):10727, 1997.

Shaw, W.D and M.T. Ozog. ‘Modeling Overnight Recreationa Trip Choice; Application of a Repeated Nested Multinomial Logit Model’, *Environmental and Resource Economics*, 13:397-414. 1999.

Train, Russell, “Mixed Logit Models for Recreation Demand” Chapter 4 in (J. Herriges and C. Kling, eds.) *Valuing Recreation and the Environment*, Edward Elgar, 1999.

U.S. Department of Commerce. NOAA. National Estuarine Inventory Data Atlas. Volume 4: Public Recreation Facilities. December 1988.

Appendix A:
Aggregation of Species into Groups

Small Gamefish

Striped Bass	Seatrout
Baracuda	Bluefish
Mackerels	Bonito
Jacks	Red Drum

Bottomfish

Sharks	Catfish	Pollack	Carp	
Sandbar	Sea Bass	Kingfish		Sea Robin
Sand Tiger	Butterfish	Spot		Pinfish
Dogfish	Porgy/Scup	Black Drum		Perch
Smooth Dog	Toadfish	Hake		
Brown Cat	Sawfish	Tautog		
Nurse	Sheepshead	Grouper		
Cat	Grunt	Cod		

Flatfish

Summer Flounder
Sole
Winter Flounder (Fluke)
Southern Flounder
Flounders

Big Gamefish

Sharks	Tunas
Blue	Sailfish
Thresher	Wahoo
Mako	Marlins
Hammerheads	Swordfish
White	Dolphin
Tiger	

Appendix B: Site Definitions

State (sites per state)	*Counties (or independent cities in Virginia)*	
Maine (8)	Cumberland	Kennebec and Sagahadoc
	Hancock	Penobscott and Waldo
	Knox	York
	Lincoln	Washington
New Hampshire (1)	Rockingham and Hudson	
Massachusetts (8)	Barnstable	Nantucket
	Bristol	Norfolk
	Dukes	Plymouth
	Essex	Suffolk
Rhode Island (5)	Bristol	Providence
	Kent	Washington
	Newport	
Connecticut (4)	Fairfield	Middlesex
	New Haven	New London
New York (10)	Bronx	Kings
	Nassau sound side	Queens
	Nassau ocean side	Richmond
	Suffolk sound side	Westchester
	Suffolk bays	Suffolk internal
New Jersey (8)	Atlantic	Cape May bay side
	Cumberland	Cape May ocean side
	Middlesex	Monmouth bay side
	Ocean	Monmouth ocean side
Delaware (4)	Kent	Sussex north of Lewes
	New Castle	Sussex south of Lewes
Maryland (7)	Anne Arundel	Charles and St. Mary's
	Calvert	Dorchester and Somerset
	Worcester	Baltimore, Cecil and Hartford
	Caroline, Kent, Queen Anne's and Talbot	

Virginia (8)	Virginia Beach Accomack and North Hampton Essex, Gloucester, King William, Mathews, Middlesex, Caroline and Fredericksburg Hampton City, Newport News, and Poquoson Isle of Wight, Suffolk and Surry James City and York King George, Lancaster, Northhumberland, Richmond, and Westmoreland Norfolk and Portsmouth